



Weed Plant Detection In Crops Using Deep Learning Technique

Dr. A. Hazarathaiah | Sk.Shahabaz | P. Supriya | S. Bhavana | R.Pranusha

Department of ECE, Narayana Engineering College, Gudur, AP, India

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ABSTRACT

In the olden days, Weed detection is a difficult task for the farmers during cultivation of the crops. Weeds are the most important biotic constraints to agricultural production in both developing and developed countries. In general, weeds present the highest potential yield loss to crops along with pathogens (fungi, bacteria, etc). Many traditional methods are implemented which are focused and identifying weed directly. This project provides a solution for the existing problem in integrating deep learning techniques in order to identify the weed plants across the vegetable plantation using CNN and advanced deep learning techniques.

Initially a trained Model was used over the data sets in order to draw the overlay by boundary boxes across the vegetable and weed leaves. The remaining space which was falling out of the overlay boundary boxes will be considered as weed through advanced detection techniques. The Convolutional Neural Network (CNN) algorithm is used to recognize the weeds by drawing the bounding boxes around the green plants and the leftover parts are identified as crops. In this way, it focuses on identifying only the vegetable crops and thus avoid handling Various Species.

KEYWORDS: Image Processing, Deep Learning, Convolutional Neural Network (CNN), YOLO -V2, Weed detection.

1. INTRODUCTION

In this current scenario, A weed is any plant that requires some form of action to reduce its effect on the economy, the environment, as well as human health. Weeds are also known as invasive plants. Weeds typically produce large numbers of seeds, assisting their spread. Vegetation is considered one of the most nutrient-dense food all around the world due to its sufficient vitamins, minerals and antioxidants. Weeds compete with crop for water, sunlight and nutrients, leaving them prone to insect and disease infestation.

The yield of Crop decreased by 45%-95% in the case of weed-crop competition. Weeds can inhabit all environments, so, it is important and responsible task to reduce the weeds in the crops. A weed can be an exotic species or a native species that colonises and persists in an ecosystem in which it did not previously exist. Weeds can inhabit all environments; from our towns and cities through to our oceans, deserts and alpine areas. Some weeds are of particular concern and, as a result, have been listed for priority management or in legislation. Throughout Australia, weeds are spreading faster than they can be controlled and management of them is

consuming an enormous amount of resources. Climate change poses an additional challenge to our ability to manage weeds. A range of management frameworks has been developed to help coordinate the management of weeds at different levels of government throughout Australia. The characteristic of weeds to be able to respond rapidly to disturbances such as climate change, may give them a competitive advantage over less aggressive species. The impacts of climate change on single species and ecosystems are likely to be complex. Climate change, as well as the interactions between climate change and other processes (such as changes to land use and to fire regimes), may also turn some currently benign species (both native and non-native) into invasive species and may lead to sleeper weeds becoming more actively weedy.

Cultural control is usually associated with farming systems, although some elements are relevant to landscape and bush care practices. It largely involves manipulating farming practices to suppress weed growth and production, while promoting the development of the desired plant. The principles and techniques used to prevent weed spread are relevant to cultural control methods to limit the spread of weeds between different land areas.

1. Physical Control

Physical control is the removal of weeds by physical or mechanical means, such as mowing, grazing, mulching, tilling, burning or by hand. The method used often depends on the area of weeds to be managed, what the land is used for, physical characteristics and the value of the land. It is important that, when using physical control, any item that can move from a weedinfested site to an un-infested site, such as machinery, vehicles, tools and even footwear, is cleaned free of weed seed before moving, to stop the spread of weeds to new areas.

2. Chemical Control

Although the use of chemicals is not always essential, herbicides can be an important and effective component of any weed control program. In some situations, herbicides offer the only practical, cost-effective and selective method of managing certain weeds. Because herbicides reduce the need for cultivation, they can prevent soil erosion and water loss, and are widely used in conservation farming.

2. AIM & OBJECTIVE

In this weed is detected from crops by using image processing. For this, we need to take a photograph of the field with good clarity to detect the weeds with more accuracy. Taking a photograph can be done by attaching a camera taking them manually. Then we will apply image processing to that image using MATLAB to detect the weed. We can detect and separate out weed affected area from the crop plants. The reason for developing such system is to identify and reuse weed affected area for more seeding. This specific area can be considered for further weed control operations, resulting in more production.

The objective of this paper was use Convolutional Neural Networks (ConvNets or CNNs) to perform weed detection in crop images and classify these weeds among grass or broadleaf, aiming to specific herbicide to weed detected.

3. LITERATURE SURVEY

Weed identification in vegetable plantation is more challenging than crop weed identification due to their random plant spacing. So far, little work has been found on identifying weeds in vegetable plantation. Traditional methods of crop weed identification used to be mainly focused on identifying weed directly; however, there is a large variation in weed species. This paper proposes a new method in a contrary way, which combines deep learning and image processing technology. There are some of the existing systems proposed by different authors are:

[1] The algorithm ("Weed Finder") estimates total density and cover of broad-leaved weed seedlings in cereal fields from near-ground red-green-blue images. The ability of "Weed Finder" to predict 'spray'/'no spray' decisions according to a previously suggested spray decision model for spring cereals was tested with images from two wheat fields sown with the normal row spacing of the region, 0.125 m.

Summary: About image analysis and computer vision

[2] In this review, we present a comprehensive and critical survey on image-based plant segmentation techniques. In this context, "segmentation" refers to the process of classifying an image into plant and non-plant pixels. Good performance in this process is crucial for

further analysis of the plant such as plant classification (i.e. identifying the plant as either crop or weed), and effective action based on this analysis, e.g. precision application of herbicides in smart agriculture applications.

Summary: About image processing and segmentation techniques.

[3]. Non-chemical weed control is important both for the organic production of vegetables and achieving ecologically sustainable weed management.

Summary: About weed management

[4]. Object detection is the most important algorithm in pattern recognition. However, there is plenty of challenging issue as the gap for algorithm improvement.

Summary: About object detection using YOLO algorithm.

4. EXISTING SYSTEM

A. Introduction

This paper has been based on the use of precision agriculture tools for the management of weeds in crops. It has focused on the creation of an image-processing algorithm to detect the existence of weeds in a specific site of crops. The main objective has been to obtain a formula so that a weed detection system can be developed through binary classifications. The initial step of image processing is the detection of green plants in order to eliminate all the soil in the image, reducing information that is not necessary.

Then, it has focused on the vegetation by segmentation and eliminating unwanted information through medium and morphological filters. Finally, a labeling of objects has been made in the image so that weed detection can be done using a threshold based on the area of detection. This algorithm establishes an accurate monitoring of weeds and can be implemented in automated systems for the eradication of weeds in crops, either through the use of automated sprayers for specific site or a weed-cutting mechanism. In addition, it increases the performance of operational processes in crop management, reducing the time spent searching for weeds throughout a plot of land and focusing weed removal tasks on specific sites for effective control.

B. Acquisition of Images

The ability to acquire own images and use them for the tests of the algorithm is advantageous, because in this way, the algorithm will adapt to the characteristics of the images obtained. It has been proposed to use a semi-professional camera of 24.2 megapixels with the ability to take photographs at 1080 pixels resolution, enough to capture good quality images.

The images were acquired at a height of 1.20 meters from the surface of the ground, this height was set to obtain a good resolution of the crop and the weeds on the surface. Each acquired image has a resolution of 4512x3000 pixels, which results in it covering an area of 180x120 cm above the crop. The position of the camera was positioned vertically to avoid shadows and ensure uniform illumination. The proposed algorithm considers the processing of images that contain uniform illumination; images with better illumination are processed with greater precision.

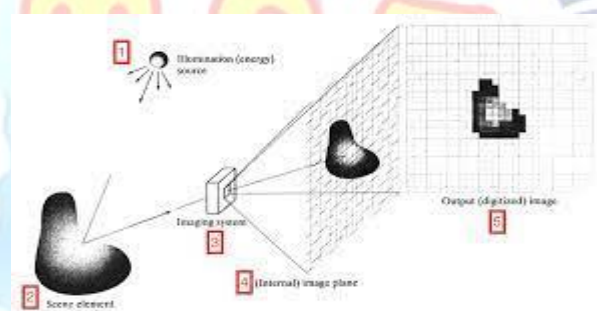


Figure 5.1: Image Acquisition

Figure 5.1. shows that the Image acquisition can be defined as the act of procuring an image from sources. This can be done via hardware systems such as cameras, encoders, sensors, etc.

C. Detection of Green Plants

Previous studies have based their criteria for selection on an index that stands out green component of source image as the NDVI (Normalized Difference Vegetation Index) and SAVI (Soil Adjusted Vegetation Index). In this project, the source image is converted to grayscale intensity whereby the hue and saturation information is eliminated while retaining the luminance, this operation can be performed through the function `rgb2gray`. Taking advantage of the RGB

components of the image, all the components in the XY space that correspond to the green value in the image, are subtracted from the grayscale image to separate the vegetation from the other components. The operation that makes this stage possible is shown in equation (1).

$$I_{Plant}(X_{Pixel}, I_{Pixel}) = I_{Green}(X_{Pixel}, Y_{Pixel}, G) - I_{Gray}(X_{Pixel}, Y_{Pixel}) \dots \dots (1)$$

D. Median Filter And Thresholding Segmentation

The median filter is used regularly to reduce noise in images with subtraction of components like the one that has been used in this process. This filter works by replacing the central pixel of a region called neighborhood, in this case a neighborhood of 3x3 pixels, creating a mask over the image. The value of the center of the mask is replaced with the calculation of the median of the values of the neighborhood pixels. This operation can be executed through the function medfilt2. Once the median filter is applied, the image must be segmented..

$$I_{bin}(x, y) = \begin{cases} 0, & I_{Median}(x, y) < t \\ 1, & I_{Median}(x, y) \geq t \end{cases}$$

Figure 5.2: Segmentation Expression

E. Morphological Filters

The classification of the labels is based on the area of each object, it is convenient to fill the holes in the objects of the image. Therefore, a filter based on morphological reconstruction should be applied in order to fill the holes and obtain a more effective area. The algorithm calculates a marked image stemming from source image borders .

$$I_{max}(x, y) = \begin{cases} 1 - I_{source}(x, y), & (x, y \text{ is on the border of } I_{source}) \\ 0, & \text{Otherwise} \end{cases}$$

Disadvantages:

- Thresholding always throws out information which you will never be able to use again, as you reduce the information to a binary variable.
- The image is noisy or it has intensity variations

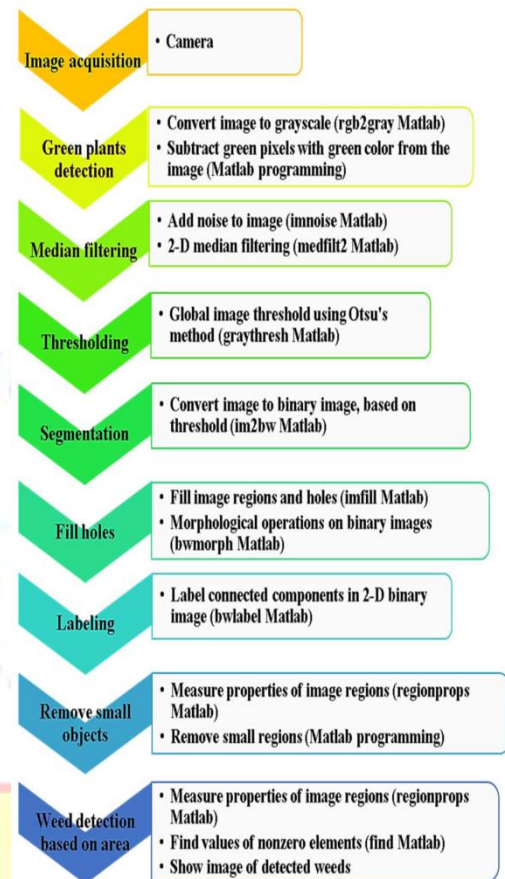


Figure 5.4: Block Diagram of Existing Method

5. PROPOSED SYSTEM

Introduction

In this Project, YOLOv2 and the details of each block in the visualization can be seen by hovering over the block. Each Convolution block has the BatchNorm normalization and then Leaky Relu activation except for the last Convolution block.

YOLO divides the input image into an SÖS grid. Each grid cell predicts only one object. In this Paper, we use Deep learning Technique to detect the weeds by using CNN method. For example, we take a crop and falls inside the grid cell. Each grid cell predicts a fixed number of boundary boxes. In this example, the grid cell makes two boundary box predictions to locate where the weed is.

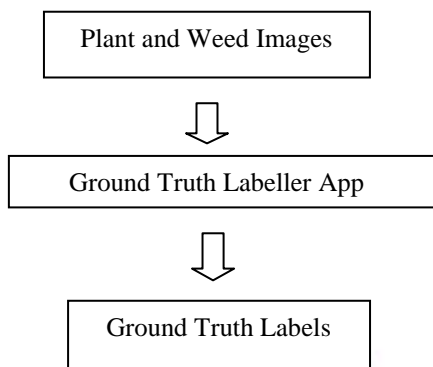


Figure 6.1: Model Diagram of Proposed Method

Proposed Algorithm YOLO_V2

In YOLOv2 the details of each block in the visualization can be seen by hovering over the block. Each Convolution block has the BatchNorm normalization and then Leaky Relu activation except for the last Convolution block. YOLO divides the input image into an S*S grid.

1	'input'	Image Input	128x128x3 images
2	'conv_1'	Convolution	16 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
3	'BN1'	Batch Normalization	Batch normalization
4	'relu_1'	ReLU	ReLU
5	'maxpool1'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
6	'conv_2'	Convolution	32 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
7	'BN2'	Batch Normalization	Batch normalization
8	'relu_2'	ReLU	ReLU
9	'maxpool2'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
10	'conv_3'	Convolution	64 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
11	'BN3'	Batch Normalization	Batch normalization
12	'relu_3'	ReLU	ReLU
13	'maxpool3'	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
14	'conv_4'	Convolution	128 3x3 convolutions with stride [1 1] and padding [1 1 1 1]
15	'BN4'	Batch Normalization	Batch normalization
16	'relu_4'	ReLU	ReLU
17	'yolov2Conv1'	Convolution	128 3x3 convolutions with stride [1 1] and padding 'same'
18	'yolov2Batch1'	Batch Normalization	Batch normalization
19	'yolov2Relu1'	ReLU	ReLU
20	'yolov2Conv2'	Convolution	128 3x3 convolutions with stride [1 1] and padding 'same'
21	'yolov2Batch2'	Batch Normalization	Batch normalization
22	'yolov2Relu2'	ReLU	ReLU
23	'yolov2ClassConv'	Convolution	24 1x1 convolutions with stride [1 1] and padding [0 0 0 0]
24	'yolov2Transform'	YOLO v2 Transform Layer.	YOLO v2 Transform Layer with 4 anchors.
25	'yolov2OutputLayer'	YOLO v2 Output	YOLO v2 Output with 4 anchors.

Figure 6.3: Layers of YOLO-V2

The boundary boxes contain box confidence score. The confidence score reflects how likely the box contains an object (objectless) and how accurate is the boundary box. We normalize the bounding box width w and height h by the image width and height. x and y are offsets to the corresponding cell. Hence, x , y , w and h are all between 0 and 1. Each cell has 20 conditional class probabilities. The conditional class probability is the probability that the detected object belongs to a particular class (one probability per category for each cell).

The class confidence score for each prediction box is computed as:

class confidence score = box confidence score * conditional class probability.....eq(2)

$$\begin{aligned}
 \text{box confidence score} &\equiv P_r(\text{object}) \cdot \text{IoU} \\
 \text{conditional class probability} &\equiv P_r(\text{class}_i | \text{object}) \\
 \text{class confidence score} &\equiv P_r(\text{class}_i) \cdot \text{IoU} \\
 &= \text{box confidence score} \times \text{conditional class probability}
 \end{aligned}$$

where

$P_r(\text{object})$ is the probability the box contains an object.
 IoU is the IoU (intersection over union) between the predicted box and the ground truth.
 $P_r(\text{class}_i | \text{object})$ is the probability the object belongs to class_i given an object is presence.
 $P_r(\text{class}_i)$ is the probability the object belongs to class_i

YOLO predicts multiple bounding boxes per grid cell. To compute the loss for the true positive, we only want one of them to be responsible for the object. For this purpose, we select the one with the highest IoU (intersection over union) with the ground truth. This strategy leads to specialization among the bounding box predictions. Each prediction gets better at predicting certain sizes and aspect ratios.

YOLO uses sum-squared error between the predictions and the ground truth to calculate

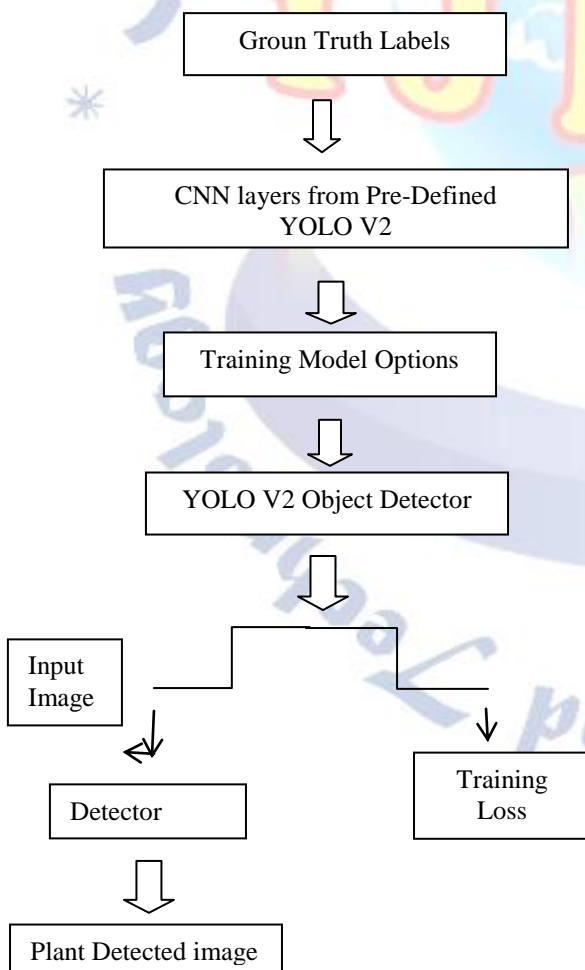


Figure 6.2:Block Diagram

loss. The loss function composes of:

- The classification loss.
- The localization loss (errors between the predicted boundary box and the ground truth).
- The confidence loss (the objectness of the box)

Convolutional Neural Network(CNN)

A convolutional neural network (CNN or ConvNet) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns

in images to recognize objects. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.

When it comes to Machine Learning, artificial neural network performs really well. Artificial Neural Networks are used in various classification task like image, audio, words.

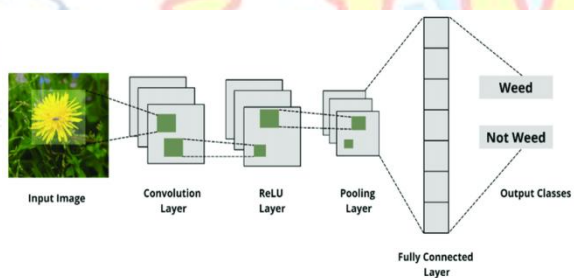


Figure 6.4: Example for CNN

Different Layers of Neural Network

Before diving into the Convolution Neural Network, let us first revisit some concepts of Neural Network. In a regular Neural Network, there are three types of layers:

1) Input Layer:

It's the layer in which we give input to our model. The number of neurons in this layer is equal to total number of features in our data (number of pixels in case of an image).

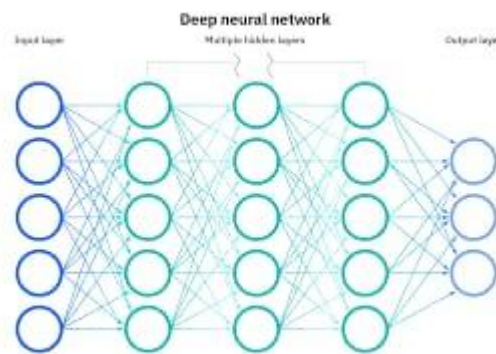
2) Hidden Layer:

The input from Input layer is then feed into the hidden layer. There can be many hidden layers depending upon our model and data size.

3) Output Layer:

The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts

the output of each class into probability score of each class.



Layers Of CNN

A Convolutional neural network (CNN) is a neural network that has one or more convolutional layers and are used mainly for image processing, classification, segmentation and also for other auto correlated data. A convolution is essentially sliding a filter over the input.

To create CNN, we have to define:

- Input Layer
- Convolutional layer
- Rectified Unit Layer
- Pooling Layer
- Dropout Layer
- Fully Connected Layer
- Output Layer

1. Input Layer:

Create an image input layer using image input layer. An image input layer inputs images to a network and applies data normalization. Specify the image size using the input Size

argument. The size of an image corresponds to the height, width, and the number of color channels of that image. For example, for a grayscale image, the number of channels is 1, and for a color image it is 3.

2. Convolution Layer:

This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size $M \times M$. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter ($M \times M$).

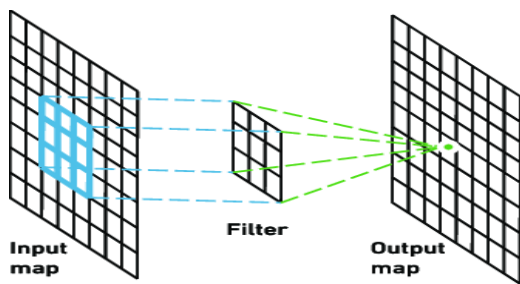


Figure 6.5: Convolution Layer

3. Rectified Linear Unit Layer:

The feature maps are passed into an activation function - just like they would be in a normal artificial neural network. More specifically, they are passed into a rectifier function, which returns 0 if the input value is less than 0 and it returns the input value otherwise.

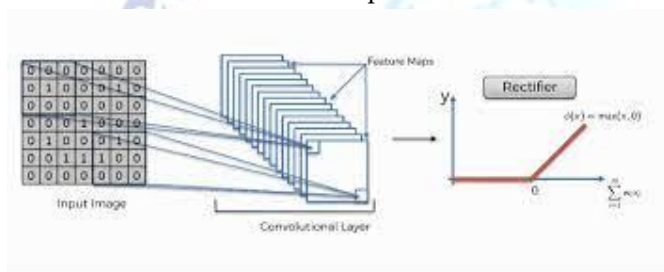


Figure 6.6: Rectified Linear Unit Layer

4. Pooling Layer:

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs.

This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. It basically summarises the features generated by a convolution layer.

5. Fully Connected Layer:

The Fully Connected (FC) layer consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers. These layers are usually placed before the output layer and form the last few layers of a CNN Architecture.

6. Output Layer:

A softmax layer applies a softmax function to the input. Create a softmax layer using softmax layer. A

classification layer computes the cross-entropy loss for multi-class classification problems with mutually exclusive classes. Create a classification layer using classification Layer. For classification problems, a softmax layer and then a classification layer must follow the final fully connected layer.

6. SIMULATION RESULTS

In this proposed method we are using the YOLO V2 model for the best object detector and the execution will be done in Matlab R2020a version.

The number of images will be taken for training the CNN and it takes the number of iterations and takes time to train a single image

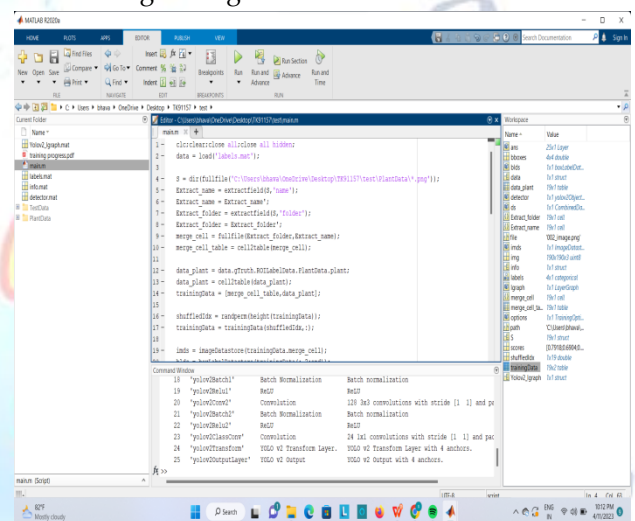


Figure 7.2. Simulation of Code

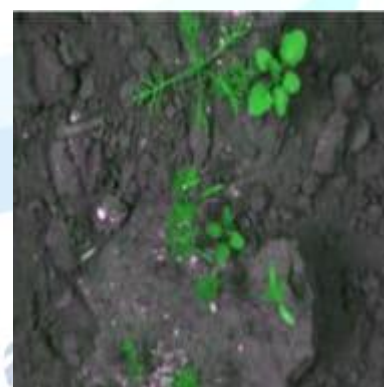


Figure 7.3. Input Image



Figure 7.4. Output Image

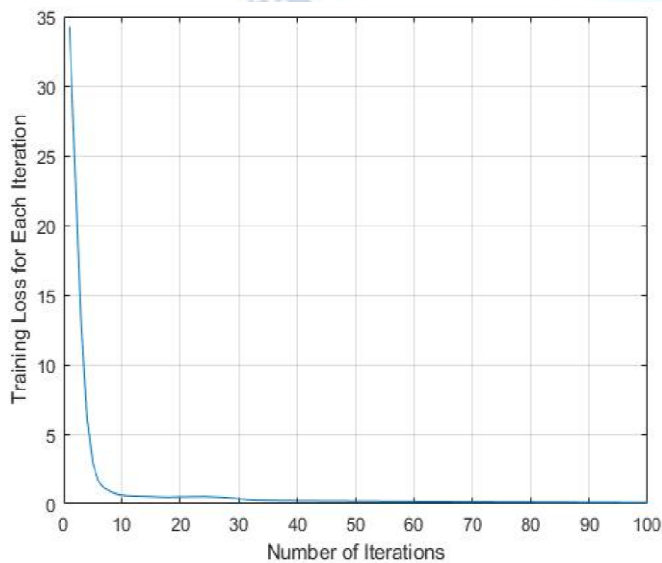


Figure 7.5. Training loss Information

7. CONCLUSION

In this Paper, we proposed an approach to identify weeds based on deep learning Technique. In this YOLO V2 divides the input image into an $s \times s$ grid. Each Grid cell predicts only one object.

FUTURE SCOPE

In this Paper, we identify only the particular labeled plant. In future by using this Deep learning there will be a chance to detect name of the plant two different objects at a time.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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